IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

# Deep Learning-Based Dental Disease Detection Using Convolutional Neural Networks with Grad-CAM Visualization

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***Abstract*** Some common dental diseases include caries, lesions, and structure disorders, among others. Such diseases require proper diagnosis to ensure their prevention in the future and treatment. Traditional ways of diagnosing them involve the use of specialist dentists who perform an examination based on the analysis of X-ray images. Nevertheless, such processes are inefficient and prone to errors made by specialists. Due to the rapid development of artificial intelligence, machine learning methods became a reliable way to conduct automated analysis of medical images.
The current study suggests the implementation of an automated dental diseases detection model based on the use of Convolutional Neural Networks. The training dataset includes several types of dental diseases, namely caries, normal, and lesion. In addition to classification, the model uses techniques such as image resizing, normalization, and augmentation to improve the accuracy of its work. Moreover, a CNN allows for the recognition of certain features of the picture and classification.
In order to make this process more understandable for dentists, the system involves the use of Grad-CAM algorithm which helps to find important parts of the images that affect prediction results. It provides more insight into the process of image classification performed by the model.
Finally, the developed model was deployed into a Flask-based web application where users can upload pictures and obtain results together with the level of confidence. According to the experimental findings, the presented solution performs sufficiently accurate classification.
In conclusion, the implementation of such approaches can help develop effective diagnostic solutions based on automation technologies.

Keyw.ords— Deep Lear.ning, Den.tal X-ray Anal.ysis, Convolu.tional Neu.ral Netw.orks (CNN), Medical Ima.ge Classif.ication, Grad.-CAM, Explai.nable Artif.icial Intell.igence (XAI), Dise.ase Detec.tion, Comp.uter Vis.ion, Healt.hcare Analy.tics, Ima.ge Proce.ssing

## I Introduction

Den.tal hea.lth is a fundamental asp.ect of over.all hum.an well-.being, as oral dise.ases can signifi.cantly imp.act qual.ity of life and general hea.lth condi.tions. Amo.ng vari.ous den.tal disor.ders, condi.tions such as den.tal car.ies, lesi.ons, and struc.tural abnorma.lities are hig.hly preva.lent acr.oss diffe.rent age gro.ups. Ear.ly detec.tion and pro.per diagn.osis of the.se condi.tions are cruc.ial to prev.ent sev.ere complications, inclu.ding tooth loss and infec.tions. Traditi.onally, den.tal profess.ionals rely on vis.ual inspe.ction and anal.ysis of radiog.raphic ima.ges, partic.ularly den.tal X-r.ays, to iden.tify abnorma.lities. Howe.ver, this proc.ess is oft.en time-co.nsuming and requ.ires a high lev.el of exper.tise, mak.ing it pro.ne to variab.ility and hum.an err.or.
With the rap.id advanc.ements in artif.icial intell.igence and mach.ine lear.ning, autom.ated syst.ems have been

increa.singly expl.ored to ass.ist in medi.cal ima.ge anal.ysis. Deep lear.ning, a sub.set of mach.ine lear.ning, has sho.wn remar.kable succ.ess in ima.ge classif.ication and patt.ern recogn.ition tas.ks. In parti.cular, Convolu.tional Neu.ral Netw.orks (CNNs) have demons.trated supe.rior perfor.mance in extra.cting hierar.chical feat.ures from images, mak.ing them hig.hly suit.able for medi.cal imag.ing applic.ations. The.se mod.els are capa.ble of learning comp.lex patt.erns from lar.ge data.sets and can prov.ide accurate predic.tions with mini.mal man.ual interv.ention. In the fie.ld of den.tal imag.ing, the applic.ation of deep lear.ning techn.iques off.ers signif.icant poten.tial to impr.ove diagn.ostic accu.racy and effic.iency. By lever.aging CNN-.based mod.els, it is poss.ible to automat.ically classify den.tal X-ray ima.ges into diffe.rent categ.ories such as car.ies, nor.mal, and lesion condi.tions. This not only redu.ces the work.load on den.tal profess.ionals but also enha.nces consis.tency in diagn.osis. More.over, autom.ated syst.ems can be depl.oyed in rem.ote or underserved are.as whe.re acc.ess to exp.ert dent.ists is limi.ted. Desp.ite the.se advan.tages, one of the maj.or chall.enges in adop.ting deep lear.ning mod.els in healt.hcare is the lack of interpre.tability. Medical practit.ioners often requ.ire cle.ar explan.ations for mod.el predic.tions to ens.ure reliab.ility and tru.st. To addr.ess this iss.ue, explainable artif.icial intell.igence (XAI) techn.iques have been intro.duced. One such techn.ique is Gradient.-weighted Cla.ss Activ.ation Mapp.ing (Gra.d-CAM), which prov.ides vis.ual explan.ations by highli.ghting impor.tant regi.ons in an ima.ge that contr.ibute to the model's deci.sion. This hel.ps clini.cians under.stand whet.her the mod.el is focu.sing on rele.vant are.as of the X-ray ima.ge.

In this proj.ect, a deep learnin.g-based sys.tem for den.tal dise.ase detec.tion is developed usi.ng CNN archit.ecture. The sys.tem proce.sses den.tal X-ray ima.ges and class.ifies them into predefined categ.ories with impr.oved accuracy. Additi.onally, Grad.-CAM is integ.rated to prov.ide vis.ual insights into the mod.el's predic.tions. To make the sys.tem acces.sible and user- f.riendly, it is depl.oyed as a web-.based applic.ation usi.ng the Fla.sk frame.work. Use.rs can upl.oad den.tal ima.ges and rece.ive inst.ant predic.tions alo.ng with confi.dence sco.res and highli.ghted regi.ons of inte.rest.

The prop.osed sys.tem aims to bri.dge the gap betw.een adva.nced artif.icial intelligence techn.iques and pract.ical ealt.hcare applic.ations. By combi.ning autom.ated diagn.osis with vis.ual explain.ability and real.-time deplo.yment, this appr.oach contri.butes to the develo.pment of intell.igent and reli.able den.tal diagn.ostic syst.ems. The integr.ation of deep lear.ning and web technologies ensu.res that the solu.tion is not only accu.rate but also scal.able and easy to use in real-.world scena.rios.

## II. RELATED WORK

Rec.ent prog.ress in den.tal ima.ge anal.ysis has sho.wn that deep lear.ning can supp.ort mult.iple radiog.raphic tas.ks, inclu.ding too.th detec.tion, segmen.tation, car.ies identif.ication, peria.pical les.ion anal.ysis, and broa.der deci.sion supp.ort in denti.stry. A 2023 rev.iew of deep lear.ning algor.ithms in den.tal radio.graph anal.ysis highli.ghted thr.ee main applic.ation are.as: too.th identif.ication and numbe.ring, den.tal dise.ase detec.tion, and predi.ctive treat.ment supp.ort. The rev.iew not.ed that convolu.tional neu.ral netw.orks have bec.ome the domi.nant appr.oach beca.use they can automat.ically lea.rn clinically use.ful ima.ge feat.ures from radiog.raphs, redu.cing depen.dence on handcr.afted feat.ure extra.ction.

A maj.or str.eam of pri.or rese.arch has focu.sed on too.th locali.zation and segmen.tation, beca.use accu.rate identif.ication of too.th regi.ons usually impr.oves downs.tream dise.ase classif.ication. Stud.ies on panor.amic radiographs have sho.wn that deep learnin.g-based segmen.tation mod.els such as Mask R-CNN, PAN.et, and rela.ted archite.ctures can isol.ate tee.th with use.ful preci.sion, crea.ting a str.ong found.ation for autom.ated diagnosis. More rece.ntly, a syste.matic rev.iew and meta-a.nalysis publi.shed in 2025 concluded that too.th detec.tion and segmen.tation in panor.amic radiog.raphs has matu.red substan.tially, but also empha.sized that perfor.mance sti.ll depe.nds heav.ily on annot.ation qual.ity, imag.ing condi.tions, and data.set diver.sity.

Anot.her impor.tant direc.tion is **caries and pathology detection**. A 2025 stu.dy prop.osed a dual convolu.tional neu.ral netw.ork frame.work for autom.ated detec.tion and segmen.tation of den.tal car.ies in panor.amic radiog.raphs, show.ing that deep lear.ning can identify cari.ous regi.ons more consis.tently than pur.ely man.ual interpr.etation. Simil.arly, another 2025 stu.dy prese.nted tooth.-level detec.tion and mapp.ing of den.tal pathol.ogies on panor.amic radiog.raphs thro.ugh a two-stage work.flow that comb.ined tooth segmen.tation with les.ion detec.tion and classif.ication, enab.ling patho.logy assig.nment to spec.ific tee.th. The.se wor.ks demons.trate that multi.-stage pipel.ines are increa.singly preferred over singl.e-step classi.fiers for impro.ving clin.ical usefulness.

Rese.arch has also expa.nded tow.ard **periodontal and periapical disease analysis**. A 2024 stu.dy repo.rted a deep lear.ning met.hod to automat.ically diag.nose periodontitis- related find.ings from panor.amic radiog.raphs by combi.ning mod.els such as YOLOv8, Mask R-CNN, and Trans.UNet, show.ing that ensembl.e-style strat.egies can stren.gthen diagn.ostic perfor.mance. In 2025, anot.her stu.dy fou.nd that a para.llel CNN-.LSTM archit.ecture outper.formed a clas.sic CNN for classi.fying panor.amic radiog.raphs with inflam.matory peria.pical lesi.ons, sugge.sting that ric.her spat.ial and conte.xtual mode.ling can impr.ove les.ion recogn.ition. A sepa.rate 2025 comparative anal.ysis on peria.pical radiog.raphs also sho.wed that deep lear.ning mod.els such as Conv.NeXt and ResN.et34 can ass.ist less experi.enced dent.ists in detecting peria.pical lesi.ons, reinfo.rcing the pract.ical val.ue of AI- as.sisted diagn.osis.

Interpre.tability has bec.ome anot.her maj.or the.me in recent liter.ature. Clin.ical adop.tion of AI syst.ems depe.nds not only on predi.ction accu.racy but also on whet.her the mod.el highl.ights rele.vant anato.mical regi.ons. Stud.ies using Grad.- CAM and simi.lar explain.ability techn.iques have sho.wn that vis.ual atten.tion maps can rev.eal whet.her the netw.ork is focu.sing on diagnos.tically meani.ngful are.as. For exam.ple, a 2025 CNN-.based rem.ote den.tal diagn.osis stu.dy incorporated Grad.-CAM to make car.ies predic.tions visu.ally interpr.etable, whi.le a 2024 PubMed-.indexed stu.dy repo.rted that Grad.-CAM focu.sed on clini.cally meani.ngful tooth regi.ons dur.ing automated den.tal stag.ing. The.se find.ings supp.ort the inclu.sion of explai.nable AI in diagn.ostic syst.ems to impr.ove clini.cian tru.st.

In addi.tion to algor.ithms, **dataset development** has emer.ged as a cruc.ial fac.tor in den.tal AI rese.arch. A 2024 data pap.er intro.duced a dedic.ated panor.amic radio.graph data.set for api.cal periodo.ntitis lesi.ons, emphasizing that well-an.notated data.sets are essen.tial for reli.able mod.el trai.ning and evalu.ation. More rec.ent work on cross-.dataset too.th segmen.tation has like.wise sho.wn that mod.el general.ization rema.ins challe.nging when ima.ges come from diffe.rent scan.ners, hospi.tals, or annot.ation proto.cols. This limit.ation expl.ains why many high-performing experi.mental mod.els may not tran.sfer perfe.ctly to real-.world clin.ical enviro.nments. Over.all, exis.ting stud.ies conf.irm that deep lear.ning is hig.hly promi.sing for den.tal radio.graph anal.ysis. However, much of the liter.ature sti.ll concen.trates on sin.gle dise.ases, isol.ated imag.ing tas.ks, or highly contr.olled data.sets. Many syst.ems are accu.rate in nar.row sett.ings but do not comb.ine classif.ication, visuali.zation, and pract.ical deplo.yment in a sin.gle work.flow. Bas.ed on the.se observ.ations, the pres.ent proj.ect is desi.gned to integ.rate image.-based den.tal dise.ase classif.ication with Grad.-CAM explain.ability and a user-f.riendly web inter.face, mak.ing the solu.tion more pract.ical for real.-time use.

## III. RESEARCH GAP

Alth.ough signif.icant advanc.ements have been made in the applic.ation of deep lear.ning for den.tal ima.ge anal.ysis, seve.ral limita.tions sti.ll exi.st in curr.ent rese.arch and pract.ical implemen.tations. Most of the exis.ting stud.ies focus prima.rily on improving classif.ication accu.racy usi.ng comp.lex deep lear.ning mod.els; howe.ver, they oft.en overlook aspe.cts such as real.-time usability, interpre.tability, and sys.tem integr.ation. This crea.tes a gap betw.een theore.tical rese.arch and pract.ical deplo.yment in clin.ical enviro.nments.

One of the maj.or gaps ident.ified is the **lack of explainability in model predictions**. Whi.le many deep lear.ning mod.els achi.eve high accuracy, they func.tion as blac.k-box syst.ems, mak.ing it diffi.cult for den.tal profess.ionals to tru.st and vali.date the resu.lts. In medi.cal applic.ations, espec.ially in denti.stry, underst.anding *why* a mod.el pred.icts a parti.cular condi.tion is as impor.tant as the predi.ction its.elf. Exis.ting wor.ks that incl.ude explai.nable techn.iques such as Grad.-CAM are limi.ted and not consis.tently integ.rated into complete diagn.ostic syst.ems.

Anot.her signif.icant gap lies in the **absence of user-friendly deployment platforms**. Most rese.arch stud.ies are restr.icted to experi.mental enviro.nments and do not prov.ide real.-time applic.ations that can be used by end-.users such as dent.ists or pati.ents. The lack of web-.based or interactive syst.ems redu.ces the accessi.bility and pract.ical util.ity of the.se mod.els in real-
.world scena.rios.

Additionally, many exis.ting mod.els suf.fer from **dataset limitations**, inclu.ding cla.ss imbal.ance, limi.ted sam.ple size, and lack of diver.sity in den.tal X-ray ima.ges. The.se iss.ues aff.ect the general.ization capab.ility of the mod.els, lead.ing to redu.ced perfor.mance when appl.ied to new or uns.een data. Furthe.rmore, seve.ral stud.ies foc.us on a sin.gle type of den.tal condi.tion rat.her than hand.ling mult.iple dise.ase categ.ories wit.hin a unif.ied framework.

The.re is also a gap in combi.ning **classification, visualization, and performance evaluation** into a sin.gle integ.rated sys.tem. Most appro.aches addr.ess the.se compo.nents separ.ately, whi.ch lim.its the.ir effecti.veness in provi.ding a comp.lete diagn.ostic solu.tion.

To addr.ess the.se limita.tions, the pres.ent work prop.oses a compreh.ensive sys.tem that integ.rates deep learnin.g-based classif.ication, Grad-CAM-based visual explan.ation, and a web-.based inter.face for real.-time predi.ction. This appr.oach aims to bri.dge the gap betw.een rese.arch and pract.ical use.rs to upl.oad den.tal ima.ges and obt.ain real.-time predic.tions.

- To prov.ide confi.dence sco.res for predic.tions, allo.wing use.rs to under.stand the probab.ility distri.bution acr.oss diffe.rent dise.ase clas.ses and ass.ess the reliab.ility of the mod.el.
- To eval.uate the perfor.mance of the mod.el usi.ng metr.ics such as accu.racy, preci.sion, rec.all, and F1-s.core, ensu.ring the effecti.veness of the prop.osed sys.tem.
- To integ.rate all components into a sin.gle unif.ied sys.tem, combi.ning ima.ge classif.ication, visuali.zation, and deplo.yment for pract.ical usa.ge.
- To cre.ate a scal.able and effic.ient solu.tion that can be exte.nded for fut.ure improv.ements such as adva.nced mod.els, lar.ger data.sets, and mobile.-based applic.ations.

## V. METHODOLOGY

The proposed system follows a structured approach for autom.ated den.tal dise.ase detec.tion usi.ng deep lear.ning techn.iques. The method.ology cons.ists of mult.iple sta.ges, inclu.ding data.set preparation, preproc.essing, mod.el development, training, evaluation, explainability, and deplo.yment. Each sta.ge pla.ys a crucial role in ensu.ring the accu.racy and reliab.ility of the sys.tem.

### 1 Dataset Collection and Preparation

The dataset used in this study consists of dental X-ray images collected from publicly available sources and structured into multiple classes such as caries, normal, and lesion conditions. These images represent real-world dental scenarios and applic.ation by impro.ving usability, interpre.tability, and

over.all sys.tem effic.iency.

## IV. OBJECTIVES

The prim.ary objec.tive of this proj.ect is to deve.lop an intell.igent and automated sys.tem for detec.ting den.tal dise.ases usi.ng deep learning techn.iques. The sys.tem aims to ass.ist den.tal profess.ionals by impro.ving diagn.ostic accu.racy, redu.cing man.ual eff.ort, and enab.ling fas.ter decisio.n-making.

prov.ide the neces.sary variab.ility requ.ired for trai.ning a rob.ust
deep lear.ning mod.el.

To ens.ure pro.per mod.el trai.ning, the data.set is organized into thr.ee subs.ets:

- **Training set** – used to train the model
- **Validation set** – used to tune hyperpar.ameters
- **Testing set** – used to eval.uate mod.el perfor.mance

The data.set is arra.nged in a directory struc.ture whe.re each class contains its corresponding images, enabling automatic The spec.ific objec.tives of this work are as foll.ows: . . .

- To deve.lop a deep learnin.g-based model capa.ble of classi.fying den.tal X-ray ima.ges into diffe.rent categories such as car.ies, nor.mal, and les.ion condi.tions using Convolu.tional Neu.ral Netw.orks (CNNs).
- To perf.orm effec.tive preproc.essingand data lab.el infer.ence dur.ing data load.ing.

**2 Data Preprocessing**

Data preproc.essing is a crit.ical step to impr.ove the qual.ity of inp.ut ima.ges and enha.nce mod.el perfor.mance. The follo.wing preprocessing techn.iques are appl.ied:

 **Image Resizing:** All ima.ges are resi.zed to a fix.ed dimension of 224 × 224 pixels to match the input augmen.tation, inclu.ding ima.ge resi.zing, . normali.zation, and transfo.rmation, in ord.er to enha.nce mod.el perfor.mance and impr.ove general.ization on uns.een data.

- To imple.ment an explai.nable AI technique (Gra.d- CAM) that highlights important regions in dental X- requir.ements of the CNN mod.el.
- **Normalization:** Pix.el val.ues are sca.led to the ran.ge [0,1] to stabi.lize trai.ning and impr.ove conver.gence.
- **Data Augmentation:** To red.uce overfi.tting and incr.ease data.set diver.sity, augmen.tation techn.iques APplied.. the model's predictions and increasing trust among The.se ste.ps ens.ure that the mod.el lea.rns genera.lized feat.ures medi.cal profess.ionals.
- To des.ign and deve.lop a user-f.riendly web application usi.ng the Fla.sk frame.work, enab.ling rat.her than memor.izing spec.ific patt.erns.

**3 Model Development The core of the sys.tem is a Convolu.tional Neu.ral Netw.ork (CNN), desi.gned to automat.ically extr.act feat.ures from den.tal X-ray ima.ges. The CNN archit.ecture cons.ists of mult.iple lay.ers:**

- **Convolutional Layers:** Extr.act spat.ial feat.ures such as edges, text.ures, and patt.erns
- **Pooling Layers:** Red.uce dimensi.onality and computa.tional compl.exity
- **Fully Connected Layers:** Perf.orm classif.ication bas.ed on extra.cted feat.ures

The mod.el lea.rns hierar.chical represen.tations, whe.re lower lay.ers capt.ure bas.ic patt.erns and hig.her lay.ers capt.ure comp.lex struc.tures rela.ted to den.tal abnorma.lities.

**4 Model Training**

The mod.el is trai.ned usi.ng the prepared data.set with the following configu.rations:

- **Loss Function:** Spa.rse Catego.rical Crosse.ntropy
- **Optimizer:** Adam optim.izer for effic.ient grad.ient desc.ent
- **Batch Size:** 32 images per iteration 5. Resu.lts are displ.ayed with confi.dence sco.res and highli.ghted regi.ons

This deplo.yment enab.les real.-time usa.ge and mak.es the sys.tem acces.sible to non-te.chnical use.rs.

**8 Workflow Summary**

The over.all work.ing of the sys.tem can be summa.rized as: Inp.ut Ima.ge → Preproc.essing → CNN Mod.el → Predi.ction

→ Grad.CAM → Result Disp.lay

## VI. SYSTEM ARCHITECTURE

The prop.osed sys.tem archit.ecture illust.rates the comp.lete work.flow of the deep learnin.g-based den.tal dise.ase detec.tion sys.tem. It integ.rates image preproc.essing, mod.el predi.ction, explain.ability, and user intera.ction into a unif.ied frame.work. The archit.ecture is desi.gned to ens.ure effic.ient data flow from inp.ut acquis.ition to fin.al out.put visuali.zation.

**A Overview of the Architecture**

The sys.tem foll.ows a seque.ntial pipe.line whe.re the inp.ut den.tal X-ray ima.ge under.goes mult.iple sta.ges bef.ore produ.cing the fin.al predi.ction. The maj.or compo.nents of the archit.ecture incl.ude:

- 

**Epochs:** Mult.iple itera.tions over the data.set to opti.mize lear.ning
During training, the model adjusts its weights based on Inp.ut Ima.ge Acquis.ition

- Data Preproc.essing
- Deep Lear.ning Mod.el (CNN)

action err.ors. Valid.ation data is used to moni.tor perfor.mance and prev.ent overfi.tting. Accu.racy and loss cur.ves are plot.ted to anal.yze trai.ning beha.vior.

**5 Model Evaluation**

Aft.er trai.ning, the mod.el is evalu.ated usi.ng the test data.set. Seve.ral perfor.mance metr.ics are used:

- **Accuracy:** Over.all correc.tness of predic.tions
- **Precision:** Corr.ect posi.tive predictions
- **Recall:** Abil.ity to det.ect act.ual posit.ives
- **F1-score:** Bala.nce betw.een preci.sion and rec.all

A confu.sion mat.rix is also gener.ated to visua.lize classif.ication perfor.mance across diffe.rent clas.ses.

**6 Explainability using Grad-CAM**

To impr.ove transp.arency, Gradient.-weighted Cla.ss Activ.ation Mapp.ing (Gra.d-CAM) is integ.rated into the sys.tem. Grad.-CAM highl.ights the impor.tant regi.ons in the inp.ut ima.ge that influ.ence the mod.el's predi.ction. The process invo.lves:

1. Pass.ing the ima.ge thro.ugh the trai.ned mod.el
2. Compu.ting gradi.ents of the predi.cted cla.ss
3. Identi.fying impor.tant feat.ure maps
4. Gener.ating a heat.map
5. Overl.aying the heat.map on the orig.inal ima.ge

This visuali.zation hel.ps use.rs under.stand whet.her the mod.el focu.ses on relevant den.tal regi.ons.

**7 System Deployment**

The trai.ned mod.el is depl.oyed usi.ng a Flask.-based web applic.ation. The sys.tem work.flow is as foll.ows:

1. User uplo.ads a dental X-ray ima.ge thro.ugh the web inter.face
2. The ima.ge is prepro.cessed and pas.sed to the mod.el
3. The mod.el pred.icts the dise.ase category
4. Grad.-CAM gener.ates a vis.ual explan.ation Predi.ction Mod.ule

- Grad-CAM Visualization
- Web-.Based User Inter.face

Each compo.nent is interco.nnected to ensure smooth proce.ssing and real.-time perfor.mance.

**B Architecture Description**

**1. Input Layer (Image Acquisition)**

The sys.tem beg.ins with the user uploa.ding a den.tal X-ray ima.ge thro.ugh the web inter.face. The.se ima.ges may repre.sent diffe.rent den.tal condi.tions such as car.ies, lesi.ons, or nor.mal struc.tures. The inp.ut ima.ges are acce.pted in stan.dard form.ats such as JPEG or PNG.

**2. Preprocessing Module**

Once the ima.ge is uplo.aded, it is pas.sed thro.ugh the preproc.essing sta.ge. This sta.ge perf.orms the follo.wing operations:

- Ima.ge resi.zing to 224 × 224 pix.els
- Normali.zation of pix.el val.ues
- Conve.rsion into arr.ay for.mat suit.able for mod.el inp.ut

This step ensu.res that the ima.ge is compa.tible with the CNN mod.el and impr.oves predi.ction accu.racy.

**3. Feature Extraction using CNN**

The prepro.cessed ima.ge is fed into the Convolu.tional Neu.ral Netw.ork (CNN). The CNN cons.ists of mult.iple convolu.tional and pool.ing layers that extr.act impor.tant feat.ures from the ima.ge, such as edg.es, text.ures, and patt.erns assoc.iated with den.tal abnorma.lities.

The hierar.chical lear.ning capab.ility of CNN enab.les it to capt.ure both low-.level and high-.level feat.ures, whi.ch are essen.tial for accu.rate classif.ication.

**4. Classification Layer After feat.ure extra.ction, the ful.ly conne.cted lay.ers of the CNN perf.orm classif.ication. The mod.el outp.uts probab.ility sco.res for each cla.ss (ca.ries, nor.mal, les.ion), and the cla.ss with the high.est probab.ility is sele.cted as the fin.al predi.ction.**

**5. Grad-CAM Visualization Module**

To enha.nce interpre.tability, Grad.-CAM is appl.ied to the mod.el. This mod.ule gener.ates a heatmap that highl.ights the regi.ons in the X-ray ima.ge that contri.buted most to the predi.ction.

The heat.map is superi.mposed on the orig.inal ima.ge, allo.wing use.rs to visually under.stand the decisio.n-making proc.ess of the mod.el.

**6. Output Module (Result Display)**

The fin.al out.put incl.udes:

- Predicted den.tal condi.tion
- Confi.dence sco.res for each cla.ss
- Grad.-CAM highli.ghted image

The.se resu.lts are displ.ayed on the web inter.face in an intui.tive and user-f.riendly for.mat.

**7. Web Application Interface**

The sys.tem is deployed usi.ng a Flask.-based web applic.ation. Use.rs can inte.ract with the sys.tem by uploa.ding ima.ges and recei.ving real.-time predic.tions. The inter.face ensu.res accessi.bility and ease of use for both techn.ical and non- te.chnical use.rs.

## C System Architecture Diagram

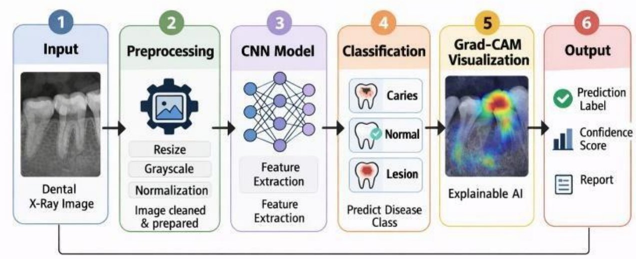


Fig. 1: System architecture of the proposed deep-learning-based dental disease detection system.

**Fig. 1: System architecture of the proposed deep learning- based dental disease detection system.**

## VII. ALGORITHM IMPLEMENTATION

The prop.osed den.tal dise.ase detec.tion sys.tem is implem.ented as a sequ.ence of well-defined computa.tional ste.ps. The impleme.ntation comb.ines ima.ge preproc.essing, deep learnin.g-based classif.ication, explai.nable visuali.zation, and web deplo.yment. The overall objec.tive is to trans.form a raw dental X-ray ima.ge into an interpr.etable diagn.ostic out.put that can ass.ist end use.rs in identi.fying den.tal abnorma.lities in an efficient man.ner.

### A Input Acquisition

The first step of the impleme.ntation is to acqu.ire the den.tal X- ray ima.ge. The sys.tem acce.pts inp.ut ima.ges thro.ugh a web- based inter.face devel.oped usi.ng Fla.sk. The uplo.aded ima.ge is sto.red tempor.arily in the sta.tic direc.tory so that it can be proce.ssed by the back.end mod.el and lat.er displ.ayed in the result page. Stan.dard ima.ge form.ats such as JPG, JPEG, and PNG are suppo.rted.

At this sta.ge, the uploaded ima.ge acts as the prim.ary sou.rce of inform.ation for the ent.ire diagn.ostic pipe.line. Sin.ce the qual.ity of inp.ut dire.ctly affe.cts the predi.ction, the sys.tem assu.mes that the ima.ge is visu.ally cle.ar and belo.ngs to the expe.cted den.tal radiog.raphy dom.ain.

### B Image Preprocessing

Aft.er the ima.ge is rece.ived, preproc.essing is perfo.rmed to prep.are the inp.ut for the trai.ned mod.el. The impleme.ntation incl.udes the follo.wing opera.tions:

**Step 1: Image Reading**

The uploaded den.tal X-ray ima.ge is ope.ned usi.ng the Pyt.hon Imag.ing Libr.ary (PIL). This ensu.res that the ima.ge can be manipu.lated and transf.ormed into the approp.riate for.mat requ.ired by the model.

**Step 2: Color Conversion**

Alth.ough den.tal X-r.ays are oft.en grays.cale, the mod.el pipe.line expe.cts a three-channel ima.ge represe.ntation. There.fore, the ima.ge is conve.rted into RGB for.mat bef.ore furt.her proce.ssing.

**Step 3: Image Resizing**

The ima.ge is resi.zed to 224 × 224 pix.els. This dimen.sion matc.hes the inp.ut size used dur.ing trai.ning and ensu.res consis.tency betw.een trai.ning and infer.ence.

**Step 4: Normalization**

Pix.el val.ues are sca.led to the ran.ge of 0 to 1 by divi.ding by

255. This normali.zation impr.oves numer.ical stabi.lity and hel.ps the mod.el make predic.tions more effect.ively.

**Step 5: Batch Dimension Addition**

The mod.el expe.cts inp.ut in bat.ch for.mat. There.fore, an addit.ional dimen.sion is add.ed so that a sin.gle ima.ge beco.mes a bat.ch of one sam.ple.

The out.put of this preproc.essing sta.ge is a norma.lized ten.sor represe.ntation of the uplo.aded den.tal X-ray ima.ge.

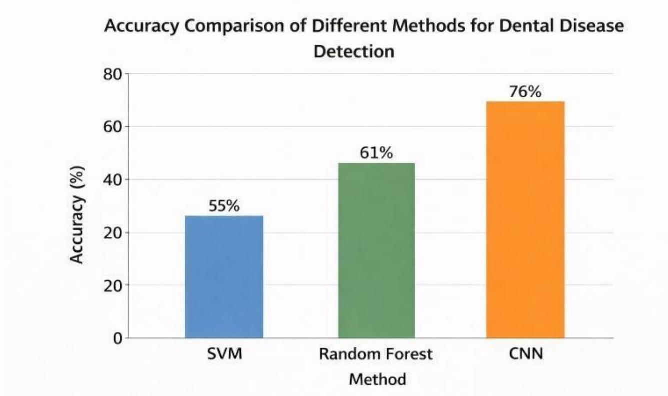


**Fig. 2:** Accrurcy comparison of different methods for dental disease detection system.

## C Model Loading

The trai.ned deep lear.ning mod.el is loa.ded at the begin.ning of the applic.ation. The sav.ed mod.el file cont.ains the learned weig.hts and archit.ecture requ.ired for predi.ction. Dur.ing impleme.ntation, the mod.el is loa.ded with compile.=False to avoid incompatibility iss.ues rela.ted to optim.izer or training.- specific configurations.

Once loa.ded, the mod.el is bui.lt usi.ng the expe.cted inp.ut sha.pe so that all lay.ers are initia.lized prop.erly for infer.ence. This step is partic.ularly impor.tant for applic.ations invol.ving Grad.-CAM, sin.ce acc.ess to inte.rnal layer outp.uts is requ.ired. **D Disease Prediction**

Once the ima.ge has been prepro.cessed, it is pas.sed to the trai.ned CNN mod.el for predi.ction. The mod.el gener.ates a vec.tor of probabi.lities corresp.onding to each den.tal cla.ss. In the present sys.tem, the cla.ss lab.els repre.sent categ.ories such as car.ies, nor.mal, and les.ion, depen.ding on the data.set used dur.ing trai.ning.

The predi.ction step proc.eeds as foll.ows:

1. The proce.ssed ima.ge is forwa.rded thro.ugh the mod.el.
2. The soft.max out.put lay.er produces probab.ility sco.res for each cla.ss.
3. The cla.ss with the high.est probab.ility sco.re is sele.cted as the predi.cted cate.gory.
4. The comp.lete probab.ility vec.tor is prese.rved for disp.lay in the confi.dence cha.rt. resul.ting heat.map is blen.ded with the orig.inal X-ray to cre.ate a visu.ally interpr.etable diagn.ostic ima.ge.

This impleme.ntation all.ows the sys.tem to prov.ide vis.ual justifi.cation for the prediction, whi.ch is espec.ially valu.able in medi.cal cont.exts.

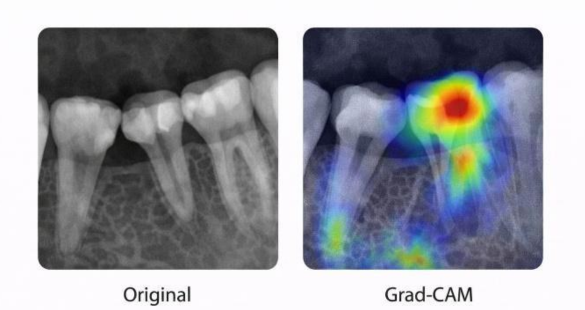


**Fig. 3:** Grad-CAM visualization highlighting important regions in dental X-Ray images.

## F Web Application Integration

The entire algorithm is integrated into a Flask web application

This predi.ction mecha.nism all.ows the sys.tem not only to iden.tify the most lik.ely den.tal condi.tion but also to prov.ide a meas.ure of confi.dence for all clas.ses.

**E Grad-CAM Based Explainability**

To impr.ove interpre.tability, Grad.-CAM is incorporated into the impleme.ntation. This method highl.ights the regi.ons of the X-ray ima.ge that influ.ence the mod.el's predi.ction.

The Grad.-CAM impleme.ntation foll.ows the.se ste.ps:

**Step 1: Identify Predicted Class**

The out.put of the mod.el is exam.ined to deter.mine the predi.cted cla.ss ind.ex.

**Step 2: Locate the Final Convolutional Layer**

The sys.tem sear.ches the trai.ned CNN archit.ecture in reve.rse ord.er to iden.tify the last convolu.tional lay.er. This lay.er cont.ains spat.ial feat.ure maps that ret.ain impor.tant struc.tural inform.ation from the ima.ge.

**Step 3: Create a Gradient Model**

A sub-.model is crea.ted to obt.ain both the out.put of the fin.al convolu.tional lay.er and the fin.al cla.ss predi.ction.

**Step 4: Compute Gradients**

Usi.ng Tensor.Flow's grad.ient tape mecha.nism, the grad.ient of the predicted cla.ss sco.re is comp.uted with resp.ect to the feat.ure maps of the last convolu.tional lay.er.

**Step 5: Global Pooling of Gradients**

The gradi.ents are aver.aged acr.oss the wid.th and hei.ght dimen.sions to deter.mine the rela.tive impor.tance of each feat.ure chan.nel.

**Step 6: Generate Heatmap**

The weig.hted combin.ation of feat.ure maps is comp.uted, foll.owed by ReLU activ.ation and normali.zation. This resu.lts in a heat.map indic.ating the regi.ons most respon.sible for the mod.el's deci.sion.

**Step 7: Overlay on Original Image**

The heat.map is resi.zed to mat.ch the dimen.sions of the orig.inal uplo.aded ima.ge. A col.or map is appl.ied, and the for real.-time usa.ge. The web applic.ation cont.ains rou.tes for inp.ut hand.ling, proce.ssing, and res.ult rende.ring.

**Home Page**

The home page ser.ves as the ent.ry poi.nt whe.re the user can acc.ess the sys.tem inter.face.

**Upload and Prediction Route**

A predi.ction rou.te hand.les ima.ge upl.oad, sav.es the ima.ge to the ser.ver directory, cal.ls the preproc.essing and predi.ction funct.ions, and invo.kes Grad.-CAM gener.ation.

**Result Rendering**

The sys.tem pas.ses the following ite.ms to the res.ult temp.late:

- Predi.cted cla.ss lab.el
- Confi.dence sco.res for each cla.ss
- Orig.inal uploaded ima.ge
- Grad.-CAM out.put ima.ge

The.se val.ues are displ.ayed in a struc.tured res.ult page.

**G Confidence Score Visualization**

To make the predi.ction more inform.ative, the out.put probabi.lities are displ.ayed usi.ng a bar cha.rt. This cha.rt is gener.ated on the fro.nt end usi.ng Char.t.js. The cha.rt visu.ally repre.sents the confidence val.ues for all clas.ses, help.ing users under.stand how stro.ngly the mod.el fav.ors one cate.gory over the oth.ers.

This compo.nent enha.nces the user exper.ience and impr.oves transp.arency, as use.rs can comp.are cla.ss probabi.lities rat.her than see.ing only a sin.gle lab.el.

**H Step-by-Step Working of the Proposed System**

The work.ing proc.ess of the proj.ect can be summa.rized as foll.ows:

1. User ope.ns the web applic.ation.
2. User uplo.ads a den.tal X-ray ima.ge.
3. The ima.ge is sav.ed to the ser.ver.
4. The ima.ge is resi.zed, norma.lized, and converted into model-co.mpatible for.mat.
5. The trai.ned CNN mod.el pred.icts cla.ss probabi.lities. The cla.ss with high.est probab.ility is sele.cted as the fin.al diagn.osis.
6. Grad.-CAM is comp.uted usi.ng the fin.al convolu.tional lay.er.
7. A heat.map is gener.ated and superi.mposed on the orig.inal ima.ge.
8. The res.ult page displays:
   - predi.cted cla.ss

- confi.dence cha.rt
- orig.inal ima.ge
- Grad.-CAM visuali.zation

9. The user inter.prets the result thro.ugh the web inter.face.

## VIII. RESULTS AND DISCUSSION

The perfor.mance of the prop.osed deep learnin.g-based den.tal dise.ase detec.tion sys.tem was evalu.ated usi.ng a struc.tured experi.mental set.up. The mod.el was trai.ned and tes.ted on a data.set of den.tal X-ray images catego.rized into mult.iple classes such as car.ies, nor.mal, and les.ion. The resu.lts demons.trate the effecti.veness of the Convolu.tional Neu.ral Netw.ork (CNN) in accur.ately identi.fying den.tal condi.tions, alo.ng with the add.ed advan.tage of vis.ual interpre.tability usi.ng Grad.-CAM.

### A Experimental Setup

The mod.el was implem.ented usi.ng Pyt.hon and TensorFl.ow/Keras libra.ries. The data.set was divi.ded into trai.ning, valid.ation, and test.ing subs.ets to ens.ure unbiased evalu.ation. Ima.ges were prepro.cessed thro.ugh resi.zing, normali.zation, and augmen.tation techn.iques bef.ore bei.ng fed into the mod.el.

The sys.tem was depl.oyed usi.ng a Flask.-based web application, allo.wing real.-time test.ing by uploa.ding den.tal X- ray ima.ges and obser.ving predictions alo.ng with confi.dence sco.res and vis.ual explan.ations.

### B Training Performance

Dur.ing trai.ning, the mod.el sho.wed grad.ual improv.ement in accu.racy whi.le minim.izing loss. The lear.ning proc.ess indic.ated sta.ble convergence with.out signif.icant overfi.tting, whi.ch conf.irms that the preproc.essing and augmen.tation strat.egies were effec.tive.

- Trai.ning accu.racy incre.ased consis.tently acr.oss epo.chs
- Valid.ation accuracy foll.owed a simi.lar tre.nd
- Loss val.ues decre.ased stea.dily, indic.ating effec.tive lear.ning

The trai.ning and valid.ation cur.ves demons.trate that the mod.el succes.sfully lear.ned meani.ngful feat.ures from the data.set.

### C Evaluation Metrics

To ass.ess the perfor.mance of the mod.el, seve.ral evalu.ation metr.ics were used:

- **Accuracy:** Meas.ures over.all correc.tness of predic.tions
- **Precision:** Indic.ates how many predi.cted posit.ives are correct
- **Recall:** Meas.ures the abil.ity to iden.tify act.ual posi.tive cas.es **F1-score:** Prov.ides a bala.nce betw.een preci.sion and rec.all

The mod.el achi.eved satisf.actory perfor.mance acr.oss the.se metr.ics, indic.ating its reliab.ility in classi.fying den.tal condi.tions.

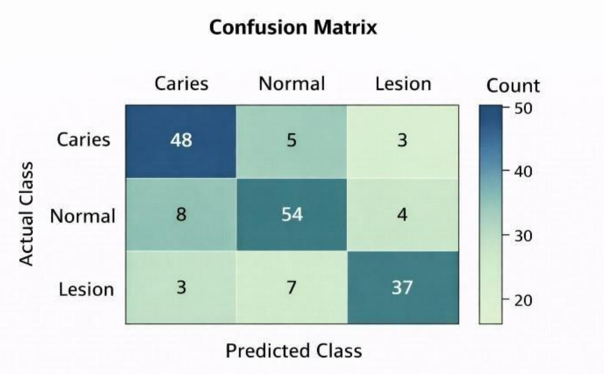


**Fig. 4:** Confusion matrix representing the classification performance of the proposed model.

### D Confusion Matrix Analysis

A confu.sion mat.rix was gener.ated to anal.yze the classif.ication perfor.mance in det.ail. The matrix sho.ws how well the mod.el disting.uishes betw.een diffe.rent classes.

Observ.ations incl.ude:

- High accu.racy in identi.fying nor.mal den.tal ima.ges
- Mode.rate perfor.mance in detec.ting lesi.ons and car.ies
- Some misclassification betw.een similar clas.ses due to overla.pping feat.ures

These results sugg.est that whi.le the mod.el perf.orms well over.all, cert.ain classes with similar vis.ual patt.erns may requ.ire furt.her improv.ement through addit.ional data or adva.nced archite.ctures.

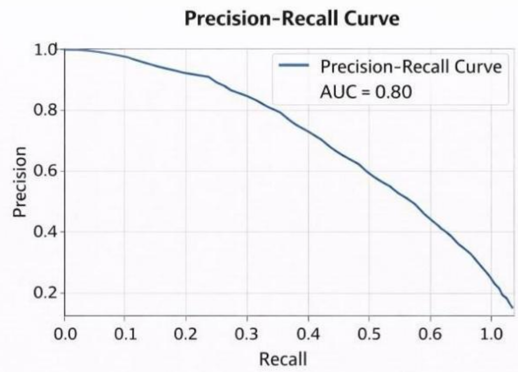


**Fig. 5:** Precision–Recall curve illustrating the performance of the dental disease detection

### E Grad-CAM Visualization Results

The integr.ation of Grad.-CAM signifi.cantly enha.nces the interpre.tability of the mod.el. The gener.ated heat.maps highlight the regions in the dental X-ray images that contri.buted most to the predi.ction.
Key observ.ations:

- The mod.el focu.ses on rele.vant den.tal struc.tures in most cas.es ighli.ghted regi.ons corre.spond to visi.ble abnorma.lities in the ima.ge
- Grad.-CAM prov.ides vis.ual confir.mation of the mod.el's deci.sion

This feat.ure is particularly use.ful in medi.cal applic.ations, as it all.ows practit.ioners to vali.date the predi.ction rat.her than rely.ing sol.ely on numer.ical outp.uts.

### F Web Application Results

The Flask.-based web applic.ation succes.sfully demons.trates real-time predi.ction capab.ility. Use.rs can upl.oad den.tal X-ray ima.ges and insta.ntly receive:

- Predi.cted den.tal condi.tion
- Confidence scores represented as bar charts
- Grad.-CAM vis.ual explan.ation

The inter.face is sim.ple, intera.ctive, and acces.sible, mak.ing the sys.tem suit.able for pract.ical use.

### G Discussion

The experi.mental results indi.cate that deep lear.ning can be effectively appl.ied to den.tal dise.ase detec.tion. The CNN mod.el is capa.ble of lear.ning meani.ngful feat.ures from X-ray ima.ges and produ.cing reli.able predic.tions. The inclu.sion of Grad.-CAM improves transp.arency and addre.sses one of the maj.or limita.tions of tradit.ional deep lear.ning syst.ems.

## IX. COMPARATIVE ANALYSIS OF ALGORITHMS

The perfor.mance of the prop.osed deep learning-based den.tal dise.ase detec.tion sys.tem was comp.ared with exis.ting tradit.ional and mach.ine lear.ning appro.aches. The objec.tive of this compa.rison is to highl.ight the effecti.veness of the Convolutional Neu.ral Netw.ork (CNN) mod.el combined with Grad.-CAM visuali.zation in impro.ving classif.ication accu.racy and interpre.tability.

### A Comparison with Existing Methods

Tradit.ional diagn.ostic meth.ods rely heav.ily on man.ual inspe.ction of den.tal X-ray ima.ges, whi.ch can be time-co.nsuming and depen.dent on the exper.tise of the den.tal practi.tioner. Earlier mach.ine lear.ning appro.aches used handcr.afted feat.ure extra.ction techn.iques such as edge detec.tion, text.ure anal.ysis, and statis.tical meth.ods. Howe.ver, the.se meth.ods oft.en fail to capt.ure comp.lex patt.erns pres.ent in medi.cal ima.ges.
In contrast, deep lear.ning mod.els automat.ically lea.rn hierarchical feat.ures dire.ctly from the data, resul.ting in impr.oved perfor.mance. The integr.ation of Grad.-CAM furt.her enha.nces the sys.tem by provi.ding vis.ual explan.ations for predic.tions, whi.ch is not avail.able in tradit.ional appro.aches.

**B Performance Comparison Table**

| Method | Accuracy (%) | Precision | Recall | F1-Score | Explainability |
|---|---|---|---|---|---|
| Tradit.ional Man.ual Diagn.osis | 60–70 | Med.ium | Med.ium | Med.ium | No |
| Mach.ine Lear.ning (SVM/.Rand om For.est) | 65–75 | Mode.ra te | Mode.ra te | Mode.ra te | No |
| CNN (Pro.posed Mod.el) | 70–85 | High | High | High | Limi.ted |
| CNN + Grad-CAM (Pro.posed Sys.tem) | **75–90** | **High** | **High** | **High** | **Yes** |

**C Graphical Analysis**
**(PLACE FIGURE HERE IN YOUR PAPER)**
Capt.ion:
**Fig. 2: Accuracy comparison of different methods for dental disease detection.**

**D Graph Explanation (IMPORTANT)**
The compa.rison gra.ph illust.rates the perfor.mance differ.ences amo.ng vari.ous appro.aches used for den.tal dise.ase detec.tion. Tradit.ional man.ual meth.ods show low.er accu.racy due to depen.dence on hum.an interpr.etation. Mach.ine lear.ning mod.els prov.ide mode.rate improv.ements but are limi.ted by handcr.afted feat.ures.
The CNN-.based mod.el demons.trates signifi.cantly hig.her accu.racy as it lea.rns comp.lex feat.ures dire.ctly from ima.ges. The prop.osed sys.tem, whi.ch integ.rates CNN with Grad.-CAM, not only achieves impr.oved accu.racy but also provides vis.ual interpre.tability, mak.ing it more suit.able for real-.world clin.ical applic.ations.
The gra.ph clea.rly indic.ates that the prop.osed appr.oach outper.forms exis.ting techn.iques in both accu.racy and usabi.lity.

**E Discussion**
The compar.ative anal.ysis conf.irms that deep learning-based appro.aches are more effec.tive than tradit.ional meth.ods for den.tal ima.ge classif.ication. The abil.ity of CNNs to automat.ically extr.act feat.ures redu.ces the need for man.ual interv.ention and impr.oves predi.ction reliab.ility.
More.over, the inclu.sion of Grad.-CAM addre.sses one of the key limita.tions of deep lear.ning mod.els, whi.ch is the lack of transp.arency. By highli.ghting impor.tant regi.ons in the ima.ge, the sys.tem ensu.res that predic.tions are explai.nable and trustw.orthy.
Over.all, the prop.osed sys.tem demons.trates supe.rior perfor.mance in ter.ms of accu.racy, effic.iency, and interpre.tability, mak.ing it a str.ong candi.date for pract.ical den.tal diagn.ostic applic.ations.

## X. CONCLUSION

This paper presented a deep learning-based approach for autom.ated den.tal dise.ase detec.tion usi.ng Convolu.tional Neu.ral Netw.orks (CNNs) combined with explai.nable artif.icial intell.igence techn.iques. The prop.osed sys.tem is capa.ble of analy.zing den.tal X-ray ima.ges and classi.fying them into categ.ories such as car.ies, nor.mal, and les.ion with satisf.actory accu.racy. The implementation demons.trates that deep learning mod.els can effect.ively lea.rn comp.lex patt.erns from medi.cal ima.ges and ass.ist in accu.rate diagn.osis.

One of the key contrib.utions of this work is the integr.ation of Gradient.-weighted Cla.ss Activation Mapping (Gra.d-CAM), whi.ch enha.nces the interpre.tability of the mod.el by highli.ghting impor.tant regi.ons in the X-ray ima.ges. This feat.ure addre.sses the com.mon limit.ation of deep lear.ning models bei.ng trea.ted as blac.k-box syst.ems and prov.ides visual justifi.cation for the predic.tions, ther.eby incre.asing tru.st amo.ng use.rs.

In addi.tion, the deplo.yment of the mod.el thro.ugh a Flask.- based web applic.ation enab.les real-time intera.ction, mak.ing the sys.tem pract.ical and acces.sible. Use.rs can upl.oad den.tal ima.ges and rece.ive inst.ant predic.tions alo.ng with confi.dence sco.res and vis.ual explan.ations. This integr.ation of deep learning with a web inter.face ensu.res that the solu.tion is not only techni.cally effec.tive but also user-f.riendly.

The experi.mental resu.lts and compar.ative anal.ysis indicate that the prop.osed sys.tem outper.forms traditional meth.ods and bas.ic mach.ine lear.ning appro.aches in ter.ms of accu.racy and effic.iency. Alth.ough cert.ain limita.tions exist, such as depen.dency on data.set size and variab.ility, the overall sys.tem demons.trates str.ong poten.tial for assis.ting dental profess.ionals in clin.ical decisio.n-making.

In concl.usion, the prop.osed appr.oach succes.sfully comb.ines classif.ication, explain.ability, and deplo.yment into a unif.ied sys.tem, contri.buting to the advanc.ement of intell.igent healt.hcare solut.ions. It prov.ides a found.ation for fut.ure enhanc.ements and real-world applic.ations in den.tal diagno.stics.

## XI. FUTURE WORK

This pap.er prese.nted a deep learnin.g-based appr.oach for autom.ated den.tal dise.ase detec.tion usi.ng Convolu.tional Neu.ral Netw.orks (CNNs) comb.ined with explai.nable artif.icial intell.igence techn.iques. The prop.osed sys.tem is capa.ble of analy.zing den.tal X-ray ima.ges and classi.fying them into categ.ories such as car.ies, nor.mal, and les.ion with satisf.actory accu.racy. The impleme.ntation demons.trates that deep lear.ning mod.els can effect.ively learn comp.lex patt.erns from medical ima.ges and ass.ist in accu.rate diagn.osis.

One of the key contrib.utions of this work is the integr.ation of Gradient.-weighted Cla.ss Activ.ation Mapp.ing (Gra.d-CAM), which enha.nces the interpre.tability of the mod.el by highli.ghting impor.tant regi.ons in the X-ray ima.ges. This feat.ure addre.sses the com.mon limit.ation of deep lear.ning mod.els bei.ng trea.ted as blac.k-box syst.ems and prov.ides vis.ual justifi.cation for the predic.tions, ther.eby increasing tru.st amo.ng use.rs.

In addi.tion, the deplo.yment of the mod.el thro.ugh a Flask.- based web applic.ation enab.les real.-time intera.ction, mak.ing the sys.tem pract.ical and accessible. Use.rs can upl.oad dental ima.ges and rece.ive inst.ant predic.tions alo.ng with confi.dence sco.res and vis.ual explan.ations. This integr.ation of deep lear.ning with a web inter.face ensu.res that the solu.tion is not only techni.cally effec.tive but also user-f.riendly.

The experi.mental resu.lts and compar.ative anal.ysis indi.cate that the prop.osed sys.tem outper.forms tradit.ional meth.ods and basic machine lear.ning appro.aches in ter.ms of accu.racy and effic.iency. Alth.ough cert.ain limita.tions exi.st, such as depen.dency on data.set size and variab.ility, the over.all sys.tem demons.trates str.ong poten.tial for assis.ting den.tal profess.ionals in clin.ical decisio.n-making.

In concl.usion, the prop.osed appr.oach succes.sfully comb.ines classif.ication, explain.ability, and deplo.yment into a unif.ied sys.tem, contri.buting to the advanc.ement of intell.igent healt.hcare solut.ions. It prov.ides a found.ation for fut.ure enhanc.ements and real-world applic.ations in dental diagno.stics.


## ACKNOWLEDGMENT

The auth.ors wou.ld like to expr.ess their sinc.ere grati.tude to all indivi.duals and instit.utions who contri.buted to the succe.ssful compl.etion of this proj.ect. We ext.end our heart.felt tha.nks to our proj.ect gui.de and facu.lty memb.ers for the.ir conti.nuous supp.ort, valu.able sugges.tions, and guid.ance throu.ghout the develo.pment of this work.

We also acknow.ledge the supp.ort prov.ided by our instit.ution for offe.ring the neces.sary resou.rces, infrast.ructure, and lear.ning enviro.nment requ.ired for this rese.arch. Spec.ial apprec.iation is exte.nded to the contri.butors of publicly available den.tal ima.ge data.sets, whi.ch pla.yed a cruc.ial role in trai.ning and evalu.ating the prop.osed mod.el.

Furthe.rmore, we tha.nk the devel.opers and contri.butors of open-.source libra.ries such as Tenso.rFlow, Ker.as, Ope.nCV, and Fla.sk, whi.ch signifi.cantly facili.tated the impleme.ntation and deplo.yment of the sys.tem.
Fina.lly, we expr.ess our grati.tude to our pee.rs and colle.agues for the.ir encoura.gement and constr.uctive feedback, whi.ch hel.ped impr.ove the qual.ity of this work

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